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Optimum Sizing of Distributed Generation and Storage Capacity in Smart Households

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Abstract—In the near future, a smart grid will accommodate customers who are prepared to invest in generation-battery systems and employ energy management systems in order to cut down on their electricity bills. The main objective of this paper is to determine the optimum capacity of a customer's distributed-generation system (such as a wind turbine) and battery within the framework of a smart grid. The proposed approach involves developing an electricity management system based on stochastic variables, such as wind speed, electricity rates, and load. Then, a hybrid stochastic method based on Monte Carlo simulation and particle swarm optimization is proposed to determine the optimum size of the wind generation-battery system. Several sensitivity analyses demonstrate the proper performance of the proposed method in different conditions.

Index Terms—Capacity planning, distributed generation, energy storage, load management, Monte Carlo simulation, particle swarm optimization (PSO), smart homes.

I. NOMENCLATURE

A. Acronyms

HEMS	Household electricity management system.
SDS	Smart distribution system.
MCS	Monte Carlo simulation.
PSO	Particle swarm optimization.
RTP	Real-time pricing.

B. Parameters and Variables

L_1	Base load in kW.
L_2	Shiftable load in kW.
L_3	Unscheduled load in kW.
EPR	Electricity purchase rate in cents/kWh.
ESR	Electricity selling rate in cents/kWh.
R_c	Rate of battery charge/discharge in kW.
DOD	Depth of battery discharge (%).

DI	Decision interval in h.
Δt	Time-step of the simulation in h.
Cap_B	Battery capacity in kWh.
Cap_B^*	Optimum battery capacity in kWh.
Cap_G	Generation capacity in kW.
Cap_G^*	Optimum generation capacity in kW.
C_G	Levelized generation cost in cents/kWh.
C_B	Levelized cost per unit of battery capacity in cents/kWh.
C_H	Total electricity cost of the residential customer in cents/day.
$E_G(\Delta t)$	Renewable generation in kWh during Δt .
$E_{Buy}(\Delta t)$	Electricity in kWh bought from the grid by the customer during Δt .
$E_{sell}(\Delta t)$	Electricity in kWh sold to the grid by the customer during Δt .
$E_B(\Delta t)$	Electricity in kWh charged in the battery during Δt .
$E_{Sell,max}$	Maximum sellback electricity limit in kWh.
$\delta(\Delta t)$	Customer electricity demand in kWh during Δt .
N	Total number of sequential time steps in MCS-PSO study.
T	Iterative duration of MCS-PSO study in h.
M	Number of particles in MCS-PSO study.
B	Available battery charge in kWh.
B_{init}	Initial battery charge in kWh at the start of iteration.
V_W	Wind speed in m/s.
V_{ci}	Cut-in wind speed of a wind turbine in m/s.
V_{co}	Cut-out wind speed of a wind in m/s.
V_r	Rated wind speed of a wind turbine in m/s.
x	Position vector of particles in MCS-PSO model.
v	Velocity vector of particles in MCS-PSO model.

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x_{gbest}	Best position vector of all particles in MCS-PSO model.
x_{pbest}^i	Best position vector of individual particle i in MCS-PSO model.
F	Fitness (objective) function.
w	Inertia weight of PSO algorithm.
C_1	Cognitive parameter of PSO algorithm.
C_2	Social parameter of PSO algorithm.
ϕ_1	Cognitive random number between 0 and 1.
ϕ_2	Social random number between 0 and 1.
N	Normal distribution.
μ_{lj}	Mean of the fitted N for load.
σ_{lj}	Standard deviation of the fitted N for load.
μ_{rj}	Mean of the fitted N for electricity rates.
σ_{rj}	Standard deviation of the fitted N for electricity rates.
$\ln N$	Lognormal distribution.
μ'_{rj}	Location parameter of fitted $\ln N$ for electricity rates.
σ'_{rj}	Scale parameter of fitted $\ln N$ for electricity rates.
WEIB	Weibull distribution.
λ_W	Scale parameter of the fitted WEIB for wind speed.
K_W	Shape parameter of the fitted WEIB for wind speed.
C. Indices	
i	Index of the particles in MCS-PSO study.
j	Index of the time steps in MCS-PSO study.
k	Index of MCS-PSO iterations.

II. INTRODUCTION

THE CONCEPT OF the smart grid is generally accepted to mean the integration of communication, computing, control, and information technologies to enhance the reliability, flexibility, efficiency, and sustainability of the electricity grid [1]. Restrictions of energy resources, aging infrastructure, environmental concerns, and increasing expectations of customers are some of the drivers of the transition toward a smarter electrical grid [2]. The advent of the smart grid will influence planning, operation, and maintenance of the power system, which is expected to become more adaptive, predictive, and distributed. Achieving this will require new infrastructure enabling the participation of active customers, accommodation of distributed generation and storage options, and incorporation of new products and intelligent control strategies [3].

Incorporation of bidirectional communication and power flow in a smart grid will provide the infrastructure and an opportunity for both the electricity providers and customers to efficiently use their assets and cut down on their costs through demand side management [4], real-time pricing [5], power sell-back opportunities [6], etc. Indeed, electricity customers of the future smart grid may no longer be perceived as passive loads. Installation of distributed energy resource (DER)-based generation, storage devices, and smart appliances will enable customers to function as integrated entities who help the grid by contributing to peak-load shaving, ancillary services, reliability improvement, and investment postponement [7]. These contributions will benefit the customers of a smart grid as well. Residential customers, for example, will be able to minimize their electricity costs by investing in renewable generation-battery systems with appropriate capacities. They will have the opportunity to buy and store electricity and sell back extra power to the grid according to the electricity rates and subject to their resource availability [6]. In addition, the ability to control end-use appliances will allow residential customers to manipulate their loads and shift part of their loads to off-peak hours using electricity management systems [8].

The challenge in minimizing the electricity costs of a smart household is determining the optimum capacities of the renewable generation-battery system best suited to that customer's electricity management system. The optimum capacities depend on various factors, such as electricity rates, stochastic behavior of renewable resources, load profile, and grid connection policies. The problem of determining the optimum capacities for different types of renewable generation and storage systems has been studied in the literature [9]–[20]. Some researchers have determined the optimum capacity for stand-alone wind generation-battery systems [9], [10]. There are some studies that have been specifically conducted for large-capacity wind turbines [11]–[13]. Meanwhile, some research [14]–[18] has been conducted to optimize the size of hybrid wind/solar or generation-battery systems which generally can be installed on the demand side of the grid with lower capacities. A number of these systems have been designed to primarily operate off grid in remote areas. For example, Ekren *et al.* [16] developed a probabilistic approach to find the optimum stand-alone solar-wind energy conversion system with battery storage in order to supply a remote cell phone base station. However, none of those studies has fully incorporated the previously described smart home features, such as load management and an electricity sell-back option, and, therefore, do not provide an optimum capacity solution from the perspective of the customers in the projected smart grid environment. Schroeder [21] have presented a stochastic method for investment optimization in a smart distribution system (SDS). However, the study was from the perspective of the distribution system operator as opposed to the customer. Likewise, in [22] the required generation capacity has been calculated from the system reliability point of view. However, that research does not include demand side management, electricity costs, or the opportunity for smart grid customers to sell electricity back to the grid.

A number of research studies have addressed demand side management in the power system [23]–[27]. Some research has

applied rule-based expert systems for load management where distributed generation and energy storage were not taken into account [23], [24]. There are some other demand management systems based on heuristic optimization methods [25] and stochastic linear programming within a dynamic pricing scheme [26]. Those approaches manage demand based on the type of loads and the electricity rates but do not include the distributed generation capabilities of the customers. Cecati *et al.* [27] considered both responsive loads and wind generation as ways to minimize the costs of distribution system operators using an energy management system. However, that approach solved an operational problem from the utility perspective and did not consider the benefits to individual households.

The main objective of our research is to develop an appropriate method for determining the optimum capacities of battery storage and renewable generation, such as a wind turbine, of a smart household, with an electricity management system, that minimizes the overall electricity cost of the household. The study outcome includes the following items:

- 1) A rule-based electricity management system (HEMS) has been proposed for a smart home to efficiently supply its loads and obtain the benefit from its available facilities and options, including renewable generation units and storage systems as well as the electricity transactions with the grid.
- 2) An optimization model has been proposed to solve the planning problem of determining the optimum capacities of the battery storage and renewable generation of the smart household using the proposed HEMS while considering the probabilistic behavior of loads, renewable energy resources, and electricity rates. The methodology presented can incorporate other demand management systems as well.
- 3) An iterative approach combining a Monte Carlo simulation process and particle swarm optimization, a MCS-PSO method has been designed to solve the optimization model and determine the optimum renewable generation and storage capacities of the smart home. The iterations in the MCS are used to capture the long-term stochastic behavior of a smart home given the expected probability distributions of load, wind generation, and electricity rates; and, at the same time, those iterations are employed by the PSO particles [28] to efficiently solve the optimization model.

Case studies are provided that validate the effectiveness of the proposed method. A variety of conditions, such as changes in distributed generation, battery costs, and electricity rates, are studied through sensitivity analysis.

It should be noted that although, for simplicity, the method introduced in this paper is described using the terms “households” and “homes,” it is not necessarily targeted and limited to residential customers. In fact, the process can be applied to other types of customers with commercial or industrial loads or microgrids in the power system by simply adjusting the variables and input parameters of the proposed model.

III. DESIGN STRUCTURE AND ASSUMPTIONS

The problem of determining the optimum capacities for generation and battery systems may be considered to be a design

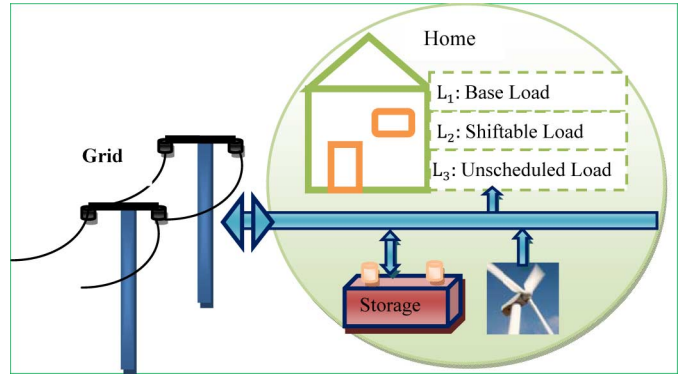


Fig. 1. Electricity flow between different sectors connected to a smart home.

problem based on long-term stochastic behavior of energy resources, load profile, and electricity rates.

The structure of a smart home is comprised of loads, small renewable generation, and a storage system, all of which are controlled by the HEMS. Fig. 1 shows a schematic of the power flow between different sectors connected to the smart home. Based on the rules defined by the HEMS, power flow is bidirectional, which means electricity may be bought from or sold to the grid at any time [6].

The models of different entities of the smart home which contribute to the electricity flow are explained in the following sections.

A. Loads

Loads in a smart home are classified into three categories, as shown in Fig. 1. The first two categories basically define the home's regular electricity consumption. The base load, L_1 , consists of end-use devices whose power usage is predetermined and nonreschedulable, such as refrigerators and most lighting. The loads in the second category, L_2 , are shiftable in time and prone to delay. Washers, dryers, and dishwashers are often among the loads which can be delayed; but the task should be accomplished by a certain deadline. Air conditioners and water heaters may be assigned to either one of the first two categories according to customer preferences and level of comfort desired. The third category, L_3 , consists of unscheduled loads which may be plugged in without any predetermined plan. Hair dryers and electric drills may be included in the last category if it is impossible for the end users to schedule their use.

B. Distributed Generation

The power output of a distributed generator is a random variable when it depends on the stochastic behavior of an energy resource. In this paper, it is assumed that the distributed generator is a small wind turbine because of the increasing number of installations and its reasonable cost in today's market [29]. The number of small wind turbines installed, which produce power primarily for residential customers and small business owners, has increased in recent years to more than 170 000 in the U.S. [29], [30]. The global installed capacity has increased 35% annually in the past few years. This growth is anticipated to be maintained at the same rate in the next couple of years and continue thereafter [31]. Other types of distributed renewable

generation, such as a photovoltaic (PV) system, may also be included without loss of generality.

At any point in time, the output of the wind generation may be used to supply the load or charge the electricity storage system. Any surplus generation can be sold directly back to the grid based on the contract between the customer and the electricity provider.

The cost of generation should be included in the total electricity cost of the home. In this paper, the cost of wind generation is considered as an average cost known as the levelized cost of generation. This cost is calculated by dividing the costs of generation, including those for installation, operation, and maintenance, over the lifetime of the wind turbine and is expressed as cents per kWh of power generation. The levelized wind generation cost depends on many factors, such as type and size of the turbine installed, availability of loans and tax credits, wind resources in the area, maintenance costs, etc.[32].

C. Electricity Storage System

An electricity storage system is critical for electricity management of the home. There are two types of tasks defined for the storage system in this paper.

Task 1: The primary task of this system is to store the surplus energy produced by wind generators, which can be used to supply future demand.

Task 2: The secondary task assigned to the storage is to provide an opportunity to make a profit from electricity trade with the grid. The rationality of this task is that the household buys and stores electricity at a low electricity rate and sells it back to the grid at a desired high electricity rate [6].

A variety of batteries with different cell technologies and prices are available on the market for use in electricity storage systems [33]. Two major factors affecting the cost of a battery are its technology and capacity. In this paper, the total expected cost of a battery is also considered as a levelized cost over its lifetime and is expressed as cents per kWh of storage capacity per hour. Meanwhile, there are a number of parameters that affect the operation or lifetime of a battery. The number of charge/discharge cycles, R_c , and DOD of the battery, are among the parameters considered in this study. R_c , and DOD represent the possible amount of battery charge /discharge per unit of time and the percentage of energy from the total capacity which can be withdrawn without damaging the battery, respectively.

D. Grid and Electricity Rates

The power grid represents a utility that provides electricity to the customers and charges them based on an RTP scheme. With the RTP, electricity market prices, which are different at each hour of the day, are provided to end customers [4] and denoted by EPR in this study. It has been indicated that real-time pricing signals will provide more operational information, enabling power system load flattening and peak demand reduction compared to other dynamic pricing methods [34]. The HEMS in this paper manages the loads, the generation, and the storage system based on the day-ahead price signals announced to the

customer. The customers may have a power contract or net metering agreement with the utility that defines the rules and rates of buying and selling power [35], [36]. These rules and grid connection requirements vary among different utilities and can address power quality and safety concerns as well [37]. It is assumed that the utility buys the excess electricity generated by its customers at ESR and provides them with electricity at EPR whenever they need it.

IV. PROPOSED RULE-BASED HOME ELECTRICITY MANAGEMENT SYSTEM

A. Data Acquisition

The data required for this planning study are the long-term expected load, generation, and electricity rates for the desired time interval of the study. There are a number of methods used previously to probabilistically forecast the electricity rates [38], load demands [39], [40], and renewable resources [41] by providing their expected probability distributions. Hence, forecasting these variables is not in the scope of this paper.

In this paper, hourly historical data for electricity rates, power demands, and wind speeds are utilized for generating their corresponding probability distributions, representing the long term behavior of these variables in each hour of a day. The probability distributions of the input variables are then sampled to generate the expected values of each variable for a particular hour in the planning horizon. Therefore, there are $N = 24$ probability distributions to model the behavior of each stochastic variable for every day of the planning horizon. A $T = 24$ -hour period was selected because first, it is the shortest duration that the tasks of the electricity management scheme, such as load shifting (all the delayed loads should be satisfied on the same day they are shifted), can be included independently; and second, the values of each stochastic variable at the same hour of different days have a good correlation such that a specific probability distribution can be defined for that variable and that hour in the long term [16], [42].

B. Rule-Based Home Electricity Management System

Fig. 2 shows how HEMS is used in each iteration of the MCS-PSO process which will be explained in more details in Section V.

There are two sets of decision rules in HEMS for obtaining the maximum benefit from the available facilities in a smart home. The first set of rules manages the overall home electricity generation, consumption, and *Task 1* of the storage system. This program starts with obtaining the statistics associated with loads, generation, and electricity rate. Then, the rules are applied to minimize the customer's electricity cost. In this scheme, if the generation is not sufficient to supply the total load ($\delta(\Delta t_j) > 0$), the decision is to discharge the battery and/or buy electricity from the grid to supply the remaining load. Otherwise, the surplus generation will eventually be stored or sold back to the grid. The remaining charge of the battery at the end of each period T is carried over to the next period.

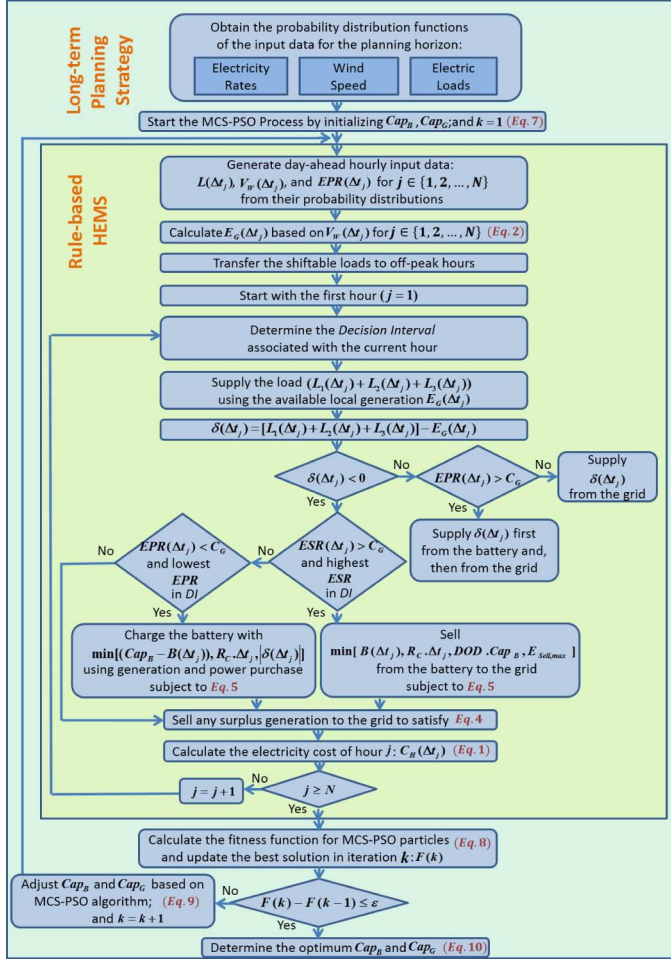


Fig. 2. Flowchart of the rule-based HEMS process within the planning strategy.

The second set of rules mutually affects the battery storage system, along with the first set of rules, to perform *Task 2* of the storage system mentioned earlier. In this study, battery charge/discharge decisions, used for electricity trade-off with the grid, are made at extrema points of some predefined dynamic intervals. These *Task 2* decision intervals (DI) are defined as being between two consecutive intersections of levelized wind generation cost (C_G) and EPR curves and may be from one to several hours long, as shown in Fig. 3. During each *Task 2* DI, the household is only allowed to buy/sell electricity from/to the grid once by charging/discharging its battery. While electricity trade using a battery is a profitable strategy for a home, the definition of DI in this scheme aims to limit the number of charge/discharge cycles to extend the battery lifetime.

Fig. 3 shows typical electricity rates, wind generation, battery decisions of *Task 2*, and a typical one-day load schedule.

The bottom curves show both the mean L_1 load, based on which the load probability distribution is defined for each hour and the resulting total load for a typical day. Due to stochastic behavior of the load, the actual load may be higher or lower than the mean base load at any hour. According to these determined variables, HEMS analyzes the amount of power surplus/deficit of the home which should be traded with the grid at each hour; and the cost of electricity is calculated accordingly.

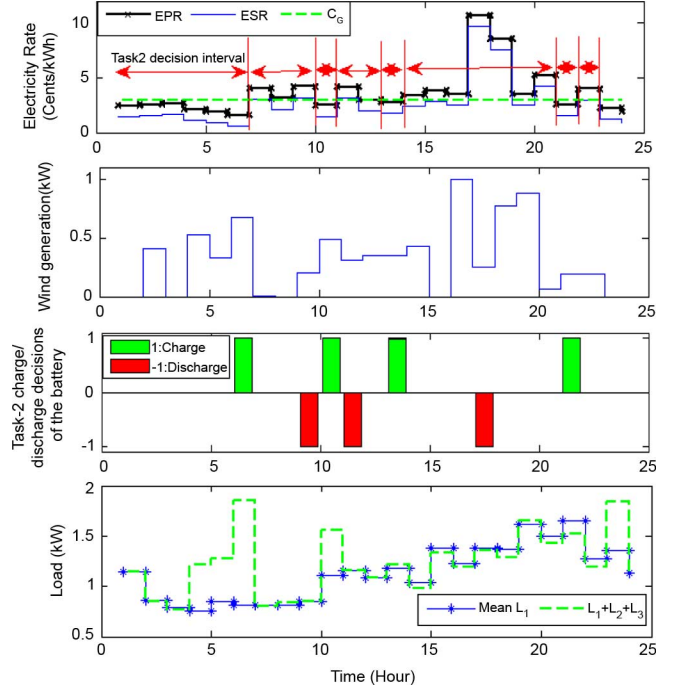


Fig. 3. Typical one-day variables determined and used by the HEMS.

V. PROPOSED MODEL AND PROCESS TO DETERMINE OPTIMUM RENEWABLE GENERATION AND STORAGE CAPACITIES

A. Optimization Model

As described before, obtaining the optimum capacity for the renewable generator and the battery is a planning problem which should include the behavior of the smart home in the optimization process. Operation of a smart home in the long run is simulated by providing load, generation, and electricity rates, at each hour of the day, as inputs to the HEMS of Fig. 2.

Applying this management system, the electricity cost of the home for j th time interval of the day, Δt_j , can be calculated by (1). The duration of each interval is one hour in this study.

$$C_H(\Delta t_j) = C_G \cdot E_G(\Delta t_j) + C_B \cdot Cap_B \cdot \Delta t + E_{Buy}(\Delta t_j) \times EPR(\Delta t_j) - E_{Sell}(\Delta t_j) \times ESR(\Delta t_j). \quad (1)$$

$E_{Buy}(\Delta t_j)$ and $E_{sell}(\Delta t_j)$ represent the amount of electricity bought/sold from/to the grid during Δt_j , which are calculated within operation of the HEMS and are functions of the wind generation and battery capacities of the home.

A simple model representing the power curve of the wind turbine [43] is employed to obtain the output power of the wind generation based on wind speed. Equation (2) is used to derive the output energy, E_G , of the wind turbine for each hour, j .

$$E_G(\Delta t_j) = \begin{cases} Cap_G \cdot \left(\frac{V_W(\Delta t_j) - V_{ci}}{V_r - V_{ci}} \right) \Delta t & V_{ci} \leq V_W(\Delta t_j) \leq V_r \\ Cap_G \cdot \Delta t & V_r \leq V_W(\Delta t_j) \leq V_{co} \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

There are cost-benefit trade-offs involved in optimum capacity calculations. Higher-capacity generators are costlier but contribute more to supplying load and reducing dependency on

grid power. The surplus generation can also be sold back to the grid. In the same way, paying more for a higher-capacity battery could be compensated for by more surplus energy storage and energy trade capability.

Therefore, the objective function to be minimized is the total electricity cost of the household, as expressed by (3).

$$F = \sum_{j=1}^N C_H(\Delta t_j). \quad (3)$$

The power flow constraint requires for any duration, Δt_j that:

$$\delta(\Delta t_j) = E_{Buy}(\Delta t_j) - E_{Sell}(\Delta t_j) - E_B(\Delta t_j). \quad (4)$$

In this equation, $\delta(\Delta t_j)$ is the electricity demand of the customer defined as the total load minus generation during Δt_j (Fig. 2). E_B is the energy charged in the battery. Therefore, negative values of represent battery discharge.

There are also some inequality constraints to comply with the operational limits of the battery, as mentioned in Section III-C, and power transfer limits, defined by (5).

$$\begin{cases} E_{Sell}(\Delta t_j) < E_{Sell,max} \\ E_B(\Delta t_j) < R_c \times \Delta t \\ -E_B(\Delta t_j) < DOD \times Cap_B \\ B(\Delta t_j) < Cap_B \end{cases} \quad (5)$$

The demand supply rules, battery charge/discharge, and power trade of the HEMS in Fig. 2 are designed to satisfy the constraints defined by (4) and (5).

B. MCS-PSO Process

Since the electricity cost of the home depends on HEMS and the inputs to the HEMS are stochastic variables obtained from their probability distributions, this cost can be generally represented by an implicit function of the following variables and parameters.

$$C_H = f(L_1, L_2, L_3, V_W, B_{init}, ESR, EPR, C_G, C_B, Cap_G, Cap_B). \quad (6)$$

The expected electricity cost of the home in the long run, with certain generation and battery capacities, can be calculated through a sequential Monte Carlo simulation. In the Monte Carlo scheme, samples from individual probability distributions of load, generation, and electricity rates are taken at each hour of the day. Using the process described for the HEMS, $C_H \Delta t_j$ is calculated and accumulated to find the total electricity cost of the day. By repeating the whole process, the expected electricity cost of the home is calculated.

Then, PSO is used to calculate the optimum Cap_G and Cap_B by minimizing an objective function. The objective function (fitness function) of the HEMS is to minimize the total expected electricity cost of the household calculated by MCS over the duration of the study. In the PSO method, initial capacities for the generation and battery are selected; and then, a population of M particles is generated to evolve toward the optimum capacities of battery and wind generation for the household. This

method has been demonstrated to be more robust and faster in finding the global solution compared with other heuristic optimization methods, such as genetic algorithms [44].

To improve the efficiency of the optimization process, an iterative procedure combining MCS and PSO methods is proposed. Using the hybrid MCS-PSO method, the input to each iteration of the PSO is stochastic and originates from the variables' probability distribution functions. Therefore, in the long run, it inherently incorporates the MCS method while it is searching for the optimum solution. The procedure can be expressed by the following steps.

1. Determine N individual probability distribution functions for different variables, such as wind speed, load, and electricity rate, according to historical data. Each function represents the probability distribution of a variable for a time step of Δt_j in the MCS-PSO where $j \in \{1, 2, \dots, N\}$.
2. Obtain C_G , C_B , and the parameters of the MCS-PSO method, such as stop criterion based on maximum number of iterations or minimum error, and the number of particles, M , in the PSO.
3. Initialize each particle by assigning two dimensional position and velocity vectors according to (7), and also initialize x_{pbest}^i , x_{gbest} , and the battery charge $B_{init}^i(K)$ for the iteration $K = 1$.

$$\begin{cases} x^i(k) = [Cap_G^i(k) & Cap_B^i(k)] \\ v^i(k) = [v_{Cap_G}^i(k) & v_{Cap_B}^i(k)] \end{cases} \quad (7)$$

where, $i \in \{1, 2, \dots, M\}$

4. For iteration k and every particle i of the population, given the current $Cap_G^i(k)$, and $Cap_B^i(k)$, do the following:
 - 4.1. Calculate the values of the loads, $L_1^i(k, \Delta t_j)$, $L_2^i(k, \Delta t_j)$, and $L_3^i(k, \Delta t_j)$, wind speed, $V_W^i(k, \Delta t_j)$, and electricity rates, $EPR^i(k, \Delta t_j)$ and $ESR^i(k, \Delta t_j)$, based on their N distinct probability distribution functions.
 - 4.2. Run the HEMS process for a duration of $T = N \cdot \Delta t$, and compute the value of the fitness function based on (3).

$$F(x^i(k)) = \sum_{j=1}^N C_H^i(k, \Delta t_j) \quad (8)$$

subject to the constraints defined by (4) and (5).

5. If $F(x^i(k)) < F(x_{pbest}^i)$, then update the values for the local optimum capacities: $x_{pbest}^i = x^i(k)$; and if $F(x^i(k)) < F(x_{gbest})$, then update the global best capacities: $x_{gbest} = x^i(k)$.

The minimum of the cost function $F(x_{gbest})$ in each iteration k has been denoted by $F(k)$ in Fig. 2.

If the stop criterion is not satisfied, update the position and velocity vectors according to (9), increase iteration k by one, and go to Step 4.

$$\begin{cases} x^i(k+1) = x^i(k) + v^i(k+1) \\ v^i(k+1) = w(k) \cdot v^i(k) + c_1 \phi_1 (x_{pbest}^i - x^i(k)) \\ \quad + c_2 \phi_2 (x_{gbest} - x^i(k)) \\ B_{init}^i(k+1) = B^i(k, \Delta t_N) \end{cases} \quad (9)$$

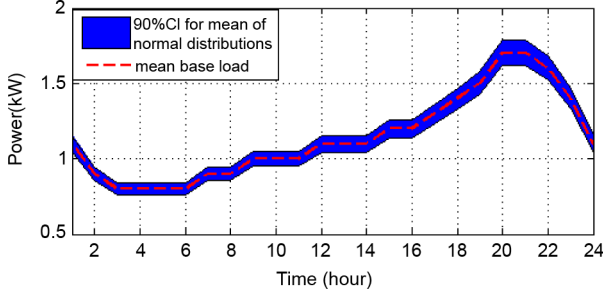


Fig. 4. Mean base load and 90% confidence interval for the mean of the fitted normal distributions in the case study.

6. Determine the optimum capacities associated with the minimum objective function.

$$\begin{cases} [Cap_G^* Cap_B^*] = x_{gbest} \\ Min \{C_H(T)\} = F(x_{gbest}) \end{cases} \quad (10)$$

VI. CASE STUDY

The case study includes a smart home with hourly loads of L_1 , L_2 and L_3 , wind generation, and a battery storage system managed by the HEMS process. The data obtained for these variables are examined using the input analyzer module of Rockwell Arena software [45] and used to generate individual probability distribution functions of these variables for each hour of a day. This section describes the assumptions and derivation of input variables for the case study.

A. Load Values

The average residential electricity consumption of a typical U.S. home [46] has been chosen for this study. L_1 , L_2 and L_3 loads are highly dependent on the electricity consumption behavior of the residents. The main appliances in the L_1 group consist of refrigerators, freezers, air conditioners, water heaters, lighting, microwave ovens, etc. [46], [47]. For the long-term study, this load is assumed to follow the normal distribution for each hour. The mean base load of this home and the 90% confidence interval for the mean of hourly fitted distributions are shown in Fig. 4. The mean and standard deviation of the distribution are described by (11).

$$L_1(\Delta t_j) \sim N(\mu_{l_j}, \sigma_{l_j}) \quad \forall j \in \{1, 2, \dots, 24\} \quad (11)$$

where $\mu_{l_j} \in [0.8, 1.77]$, $\sigma_{l_j} \in [0.05, 0.15]$

The demand considered for the schedulable L_2 group of loads is shown in Table I. These loads are randomly distributed throughout the week in a way that complies with their usage frequency. Electric vehicle, for example, is one of the schedulable loads in this case study and consumes 4 kWh with an average commute of 15 miles/day [48]. It is also assumed that all L_2 loads are scheduled to be accomplished during 24 hours.

In addition, during each hour, there are some expected L_3 loads, including TV, personal computer, some lighting, etc., which randomly change based on the uniform distribution, not exceeding 5% of the L_1 .

TABLE I
L₂ LOADS CONSIDERED FOR THE CASE STUDY

Device	Total Energy (kWh)	Usage Frequency	Duration (Hours)
Washing machine	0.5	Twice a week	1
Clothes dryer	1.1	Twice a week	1
Dishwasher	1.2	Every day	2
Electric oven	2	Once a week	1
Electric vehicle	4	Every day	4
Iron	1	Once a week	1

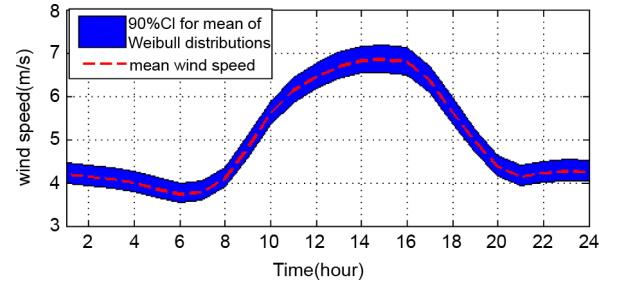


Fig. 5. Mean wind speed and 90% confidence interval for the mean of the fitted Weibull distributions in the case study.

B. Wind Generation Values

For wind speed analysis, the available three-year hourly wind speed data of McCook, Nebraska, at 10-meter elevation were used [49]. The annual average wind speed of the area is 5 m/s. The data were binned with the wind speed intervals of 0.5 m/s. The analysis results show that, for each hour, wind speeds can be best fitted into a Weibull distribution as denoted by (12). Therefore, 24 pairs of shape and scale parameters were generated for these fitted Weibull distributions with a maximum square error of 1%. The mean wind speed of the data of this case study is shown in Fig. 5.

$$V_w(\Delta t_j) \sim WEIB(\lambda_{Wj}, K_{Wj}) \quad \forall j \in \{1, 2, \dots, 24\} \quad (12)$$

where $\lambda_{Wj} \in [4.22, 7.61]$, $K_{Wj} \in [1.65, 2.35]$

C. Electricity Rates (EPR and ESR)

The EPR data were derived from the historical data of Ameren utility rates in Illinois for a duration of one year based on its rate for Zone 1 customers. The hourly data of EPR are available on Ameren's website [50]. The annual average and maximum EPR were 3.2 cents/kWh and 10.7 cents/kWh, respectively.

Similar to wind analysis, the EPR for each hour was separately analyzed and fitted to a probability distribution. The results indicate that these hourly electricity rates can best fit into either a normal or lognormal probability distribution described by (13), with the mean values shown in Fig. 6.

$$\begin{aligned} EPR(\Delta t_j) &\sim N(\mu_{rj}, \sigma_{rj}) \quad \forall j \in \{1, 2, \dots, 6\} \cup \{22, 23, 24\} \\ EPR(\Delta t_j) &\sim \ln N(\mu'_{rj}, \sigma'_{rj}) \quad \forall j \in \{7, 8, \dots, 21\} \end{aligned} \quad (13)$$

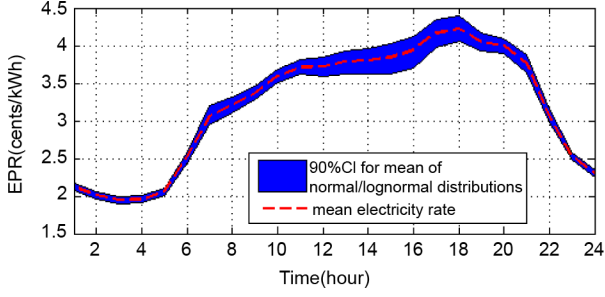


Fig. 6. Mean EPR and 90% confidence interval for the mean of the fitted distributions in the case study.

TABLE II
INPUT PARAMETERS OF THE BASE CASE STUDY

Parameter	C_G	C_B	R_c	DOD	ΔR	$E_{sell}(\max)$
Value	3.5	0.3	2	85	1.5	15
Unit	$\frac{\text{cents}}{\text{kWh}}$	$\frac{\text{cents/kWh of capacity}}{\text{Hour}}$	$\frac{\text{kWh}}{\text{Hour}}$	%	$\frac{\text{cents}}{\text{kWh}}$	$\frac{\text{kWh}}{\text{day}}$

where $\mu_{r_j} \in [0.8, 1.77]$, $\sigma_{r_j} \in [0.05, 0.15]$, and $\mu'_{r_j} \in [0.8, 1.77]$, $\sigma'_{r_j} \in [0.05, 0.15]$

As mentioned before, the price at which the customers sell electricity back to the grid is denoted by ESR. This rate is lower than EPR, and it is assumed to follow EPR by a constant difference of ΔR in this paper. A sensitivity analysis was run to consider different values of ΔR .

VII. RESULTS AND DISCUSSIONS

The previously described MCS-PSO method has been applied to the case study. The total number of simulation iterations was 10 000, which ensured the convergence of the simulation. The cognitive and social parameters of the PSO method were selected to be 2.5 and 1.5, respectively; the population of the particles was 20; the problem space was bounded by the maximum capacities of 15 kW for the wind generator and 15 kWh for the battery; and, the maximum velocity of the particles was limited to 20 percent of the maximum capacities of the wind generator and the battery. The definition of the parameters of the PSO method can be found in [51], [52]. Proper behavior of the proposed method was captured through sensitivity analysis to a number of input parameters. The following case studies have been defined to demonstrate the results of the proposed method.

A. Case 1 (Base Case)

The study parameters chosen for the base case are provided in Table II[32], [33].

The results of the MCS-PSO study indicate that a wind turbine of 3 kW and a battery of 4.5 kWh are the optimum choices for this home, and the electricity cost of the smart home would be 65.4 cents per day. In addition, the results for this case show that the optimum plan would save an average of 25 percent compared to a conventional home with the same average load without battery and generation.

TABLE III
MINIMUM C_H BY INCREASING ΔR AND $E_{sell, \max}$

Increment	+10%	+20%	+30%	+50%
Minimum C_H with change in ΔR	71	76.3	80	86.1
Minimum C_H with change in $E_{sell, \max}$	63.8	61.6	59.4	50.9

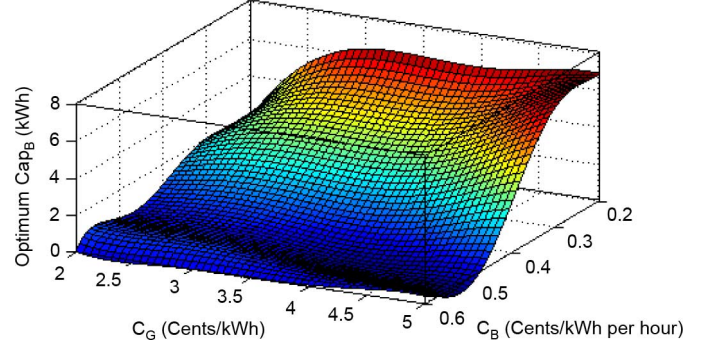


Fig. 7. Optimum battery capacity with different leveled costs of wind generation and battery.

B. Case 2 (Sensitivity to ΔR and $E_{sell, \max}$)

Several sensitivity tests show how the contract constraints, such as ΔR and $E_{sell, \max}$, affect the electricity cost of a household. By increasing these two parameters from their base values, the optimum capacities were derived; and the minimum C_H in cents per day is provided in Table III.

As ΔR increases, ESR becomes smaller; and as a result, the profit from electricity sell-back becomes less appealing. With a 50% increment in ΔR , electricity cost of the home rises by a factor of about 30% compared with the base case.

On the other hand, by raising the cap of electricity sell-back to the grid, homes would have the opportunity to benefit more from their wind generation and storage system. With a 50% increment in $E_{sell, \max}$, the home could reduce its electricity cost by 22%.

C. Case 3 (Sensitivity to Both C_G and C_B)

In this case, the effect of both C_G and C_B on the optimum capacities of a wind generator and battery is studied.

Fig. 7 shows the optimal surface of the battery capacity with different storage and wind generation costs. As C_B decreases, the optimum point is shifted toward higher battery capacities (from 0 to about 7 kWh). In addition, as the cost of wind generation increases, larger batteries become relatively more efficient than wind generators. It is observed that the optimization process prefers to choose the highest battery capacity when the battery cost is at its minimum and the wind generation cost is at its maximum value.

Similarly, Fig. 8 shows the effect of leveled costs of generation and battery on optimum capacity of the wind turbine.

Contrary to Fig. 7, the cost of a battery does not have a considerable effect on the generator capacity. On the other hand, as the cost of generation decreases, higher-capacity wind turbines become more beneficial. In this graph, the generation cost of about 3.5 cents/kWh acts like a turning point at which there is a high slope toward higher wind generation capacities. This is because, as mentioned earlier, the average EPR of this case study is 3.2

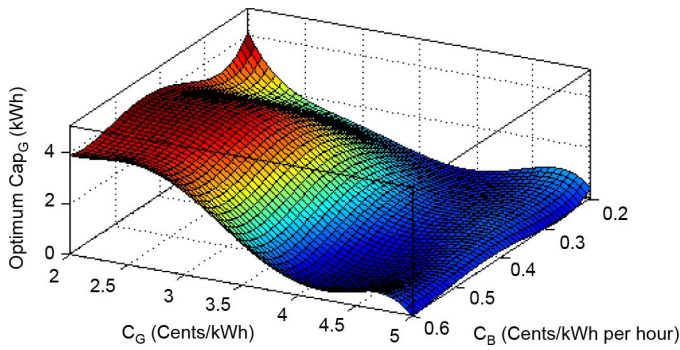


Fig. 8. Optimum wind generator capacity with different levelized costs of wind generation and battery.

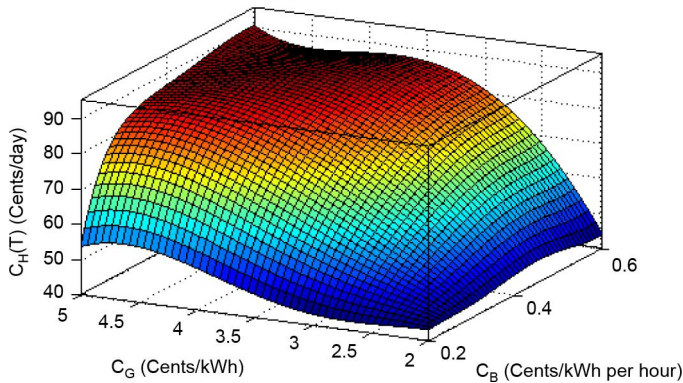


Fig. 9. Minimum electricity cost of the home with different levelized costs of wind generation and battery.

cents/kWh; and, therefore, generation costs less than this rate become exceedingly appealing. As a result of the optimization process, the minimum household electricity costs are computed and plotted in Fig. 9.

As expected, the electricity cost of the home is highest when both are at their maximum values. An interesting result is achieved by comparing the electricity cost in this figure with one of a conventional home without a generation-storage system. In the case of a conventional home, the electricity cost is 92 cents/day, which is close to the value of the smart home with a of 5 cents/kWh and a of 0.6 cents/kWh per hour. Therefore, we expect that beyond this operating point, no additional savings can be achieved by investing in a wind generator and battery, indicating the corresponding optimum capacity of the wind generator and battery should be almost zero, as justified by the results shown in Figs. 7–8.

D. Case 4 (Sensitivity to EPR)

In this case, the sensitivity of the capacities and electricity cost of the home for the base case with different electricity rates have been studied; and the results are plotted based on shape-preserving interpolation in MATLAB.

According to the results shown in Fig. 10, as EPR is increasing, an increasing trend toward higher generation-battery capacities is observable. In this case, when EPR decreases toward 2.5 cents/kWh, there is less incentive to invest in high capacity wind generators and batteries because, as depicted in the

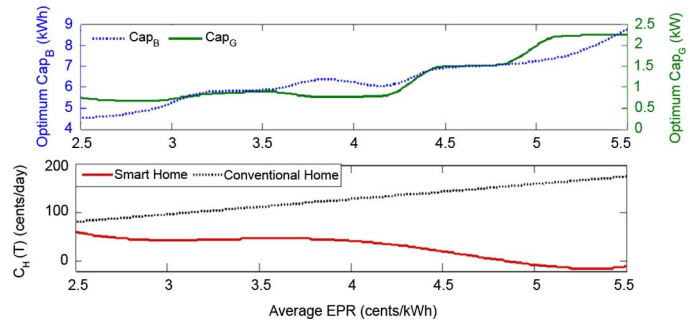


Fig. 10. Sensitivity of wind generation-battery capacities (top) and the electricity cost of the home (bottom) to the change of average EPR.

bottom plot of Fig. 10, the minimized electricity costs of the smart home and the conventional home get closer.

It is notable that as the electricity cost of a conventional home rises with a higher EPR, the electricity cost of the smart home decreases. The difference between these two costs is more noticeable at electricity rates higher than the levelized cost of wind generation where the electricity cost of the smart home has a higher rate of decrease. Homes are even able to make a profit from selling their power to the grid at an average EPR of 5 cents/kWh; because beyond this point, the cost of wind generation becomes less than the average ESR (with a of 1.5 cents/kWh). This is achieved as a result of proper utilization of the wind turbine and the battery system.

VIII. CONCLUSION

In this paper, a stochastic method was proposed to determine the optimum size of a wind generation-battery system in the context of a smart home. The solution approach comprised three stages: In the first stage, a household used a rule-based electricity management system which could effectively manage various types of its load, generation, and electricity storage, and trade power with the grid. The time-variant inputs to this system were wind speed, three categories of load, and electricity rates. In the second stage, an optimization problem was formulated where for planning purposes, the stochastic variables were represented by their individual expected probability distributions for each hour of a day. Using the proposed hybrid MCS-PSO approach in the third stage, the optimum sizes of the wind generator and battery were obtained so that the overall electricity cost of the home was minimized.

The method described can help residential customers and small business owners decide on investing in the right amount of renewable generation and battery capacities that are optimized according to their load profile, renewable resource availability, and electricity rates. Results also indicate that given the levelized costs of a wind generation and battery storage system, an average electricity rate may exist at which investing in these systems will no longer be beneficial. Sensitivity analyses were conducted to investigate the effects of electricity rates as well as wind generation and electricity storage costs on optimum capacities of a wind turbine and battery for a smart home. The results show how the customer could benefit from higher capacities of wind generation and battery as their associated costs drop. It was also illustrated that if certain conditions are met in the system, the smart grid customer has an opportunity

to make proper investments and profit from selling generation back to the grid as well.

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